

Link Scheduling in Wireless Powered Communication Networks

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Abstract—We consider a Hybrid Access Point (HAP) that is equipped with a Successive Interference Cancellation (SIC) radio, and Radio Frequency (RF) energy harvesting devices. The HAP is responsible for charging and collecting data from these devices. A fundamental problem at the HAP is scheduling uplink transmissions. In particular, given a number of transmission schedules where devices are scheduled into one or more uplink time slots, the HAP needs to select the best transmission schedule that yields the highest average sum-rate. To this end, we outline a discrete optimization approach that allows the HAP to learn the best transmission schedule over time *without* using any Channel State Information (CSI). Our results show that the HAP is able to learn the best transmission schedule with an average throughput that is of 50% higher than Slotted Aloha.

I. INTRODUCTION

The future Internet of Things (IoT) ecosystem will be populated with energy harvesting low-power sensor devices that process and send data they have acquired from their environment [1]. These IoT networks are likely to comprise of Wireless Powered Communication Networks (WPCNs) where there is a Hybrid Access Point (HAP) and Energy Harvesting Devices (EHDs); see Figure 1. The HAP uses a *harvest-then-transmit* protocol [2], where it first charges EHDs for some time period. EHDs then use the harvested energy to carry out one or more tasks. The HAP then assigns an uplink data transmission slot to each EHD for data collection. One approach to improve uplink transmissions capacity is to employ Successive Interference Cancellation (SIC) [3] at the HAP. This allows the HAP to decode multiple signals or transmissions assuming these signals meet a given set of Signal-to-Interference-plus-Noise Ratio (SINR) conditions; see Section III for details. Meeting these conditions, however, requires the HAP to have Channel State Information (CSI) to/from devices that allows it to set the transmission power of EHDs or group them according to their harvested energy and channel gain. This assumption is strong as it requires the HAP to first charge EHDs, and assuming EHDs have received sufficient energy, receive and respond to pilot symbols.

In this paper, we do not require the HAP to have CSI. Our goal is to determine an uplink transmission schedule whereby the HAP pre-assigns one or more EHDs into each time slot. Each EHD then transmits with all their harvested energy. The problem at hand is to determine the *best* transmission schedule that yields the highest average sum-rate at the HAP. To illustrate our problem, consider the WPCN shown in Figure 1.

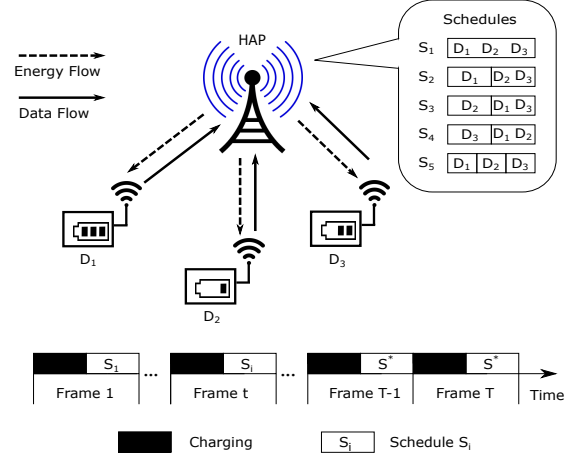


Fig. 1. A WPCN with three EHDs D_1 , D_2 and D_3 , and five transmission schedules S_1 , S_2 , S_3 , S_4 and S_5 . In each frame t , all EHDs transmit data to the HAP using the transmission schedule provided by the HAP. The best transmission schedule is denoted as S^* .

There is a half-duplex HAP and three EHDs; namely D_1 , D_2 and D_3 . Also shown are five transmission schedules. The HAP is responsible for charging the EHDs via RF and prescribing *one* of these available transmission schedules for collecting data from EHDs. We see the HAP applying a transmission schedule in each frame and finally learning the optimal or best transmission schedule S^* . Our problem is challenging as the HAP needs to select a transmission schedule without using CSI. If the HAP selects a schedule arbitrarily, it may find many SIC failures. Consequently, the chosen transmission schedule will have a very low sum-rate.

Henceforth, in this paper, we formulate a discrete optimization problem and outline an efficient solution that allows a HAP to find the best transmission schedule despite not having CSI. From numerical results, The best schedule derived by our solution outperforms Slotted Aloha by 50% in terms of average throughput. It also achieves nearly twice the average throughput of the Time Division Multiple Access (TDMA) schedule where each time slot contains only one EHD.

Next, we discuss prior works, followed by our system model in Section III. Our problem is presented in Section IV. Section V presents our approach. Our evaluation and results are presented in Section VI. We conclude in Section VII.

II. RELATED WORKS

There are many works that have considered uplink transmissions in Non-Orthogonal Multiple Access (NOMA)-based WPCNs. Their focus is to optimize the transmission power and time of either the HAP or EHDs to achieve one or more objectives. Example works include [4]–[6] and [7]. In all these above works, a fundamental difference to us is that their HAP has perfect CSI to/from EHDs. In fact, very few works have considered imperfect or unknown CSI. In [8], the authors consider channel estimation errors when optimizing the sum-rate of a WPCN. In [9], the authors study robust allocation of charging and transmission duration over a non-linear energy harvesting model. A number of works have considered statistical CSI. For example, in [10], the authors consider downlink transmissions in a multi-carrier NOMA system. The problem is to allocate a robust transmission power that satisfies the minimum rate of users with a given probability. The authors of [11] study the outage probability and optimal decoding order at receivers when a transmitter knows the average CSI. These works, however, do not consider RF charging. Moreover, they do not consider link scheduling and nodes with SIC capability.

III. SYSTEM MODEL

We consider a WPCN with one HAP and K EHDs. We use D_k , where $k \in 1, \dots, K$, to denote a EHD. The HAP uses a fixed transmission power of P . Each EHD has a rechargeable battery with a maximum capacity of \mathcal{B} . We assume EHDs use all their harvested energy whenever they transmit to the HAP. Time is divided into T frames. Each frame $t \in 1, \dots, T$ has a fixed duration of τ . Each frame consists of a charging phase and a transmit phase. The transmit phase is further divided into upload slots, which will be discussed later. We use τ_D and τ_U to denote the charging time slot and uplink data transfer duration, respectively. For each frame t , we use g_k^t to denote the channel gain from the HAP to an EHD D_k . We assume block fading channel where g_k^t varies independently across frames but remain constant in each frame. We also emphasize that the HAP has imperfect channel gain information. The path loss \mathcal{L}_k from the HAP to EHD D_k is governed by the log-distance path loss model. That is,

$$\mathcal{L}_k = \frac{d_0^\alpha 10^{(-\mathcal{L}_0 - \mathcal{X}^t)/10}}{d_k^\alpha} \quad (1)$$

where \mathcal{L}_0 is the path loss at reference distance d_0 ; i.e., $\mathcal{L}_0 = (4\pi d_0/\lambda)^2$, where λ is the wavelength. The Euclidean distance between the HAP and EHD D_k is denoted as d_k . The constant α is the path loss exponent and \mathcal{X}^t is a normal Gaussian distributed variable with zero mean and standard deviation σ (in dB). The channel coefficient is given by the complex random variable $h_k \sim \mathcal{CN}(0, 1)$.

For an EHD D_k at frame t , its received power is,

$$P_k^t = P g_k^t = P \mathcal{G}_0 \mathcal{G}_k \mathcal{L}_k |h_k^t|^2 \quad (2)$$

where \mathcal{G}_0 and \mathcal{G}_k are the antenna gains of the HAP and the EHD D_k , respectively. We consider a practical non-linear

energy harvesting model. Let $\phi(\cdot)$ be a function that takes as input the received power at the antenna of an EHD and returns the output power from the RF harvester; see [12] for details and its parameters Z , ζ_1 , ζ_2 . Device k 's harvested energy in frame t is,

$$E_k^t = \text{MIN}\{\tau_D \phi(P_k^t), \mathcal{B}\} \quad (3)$$

The HAP is responsible for informing EHDs of their uplink data transmission schedule. This allows the HAP to collect data from each EHD. We assume EHDs always have data to transmit. Let S_i denote a transmission schedule that contains one or more EHDs assigned to a time slot. We record the collection of transmission schedules in the set Φ . As an example, assume there are three EHDs: D_1 , D_2 and D_3 . In order to ensure all EHDs transmit once in a frame, we have the following possible transmission schedules: $S_1 = \{\{D_1, D_2, D_3\}\}$, $S_2 = \{\{D_1, D_2\}, \{D_3\}\}$, $S_3 = \{\{D_1, D_3\}, \{D_2\}\}$, $S_4 = \{\{D_1\}, \{D_2, D_3\}\}$ and $S_5 = \{\{D_1\}, \{D_2\}, \{D_3\}\}$. In the foregone example, we have $\Phi = \{S_1, S_2, S_3, S_4, S_5\}$. In each uplink slot, the set of transmitting EHDs belong to a *transmission set*. For example, for the schedule S_1 , there are three simultaneous transmissions over one slot. The length of each transmission schedule is denoted as $|S_i|$; e.g., $|S_5| = 3$ slots. We refer to each slot using ω and use $\mathcal{C}(S_i, \omega)$ to denote the transmission set of schedule S_i in slot ω . Recall that EHDs transmit with all their harvested energy. Therefore, the received power at the HAP from EHD D_k can be calculated as follows: $\gamma_k^t = \frac{E_k^t}{\tau_U / |S_i|} g_k^t$, where the term $\frac{\tau_U}{|S_i|}$ corresponds to the duration of each upload slot when using schedule S_i .

We assume the HAP supports SIC [3]. To ensure SIC is successful, the received power of signals must be sufficiently different from each other to ensure each transmission satisfy their SINR threshold. We now explain the SIC process. Let the transmission set $\mathcal{C}(S_i, \omega)$ contain M transmitting EHDs with index $k = 1, \dots, M$, and received power that is ordered as follows: $\gamma_1^t \leq \gamma_2^t \leq \dots \leq \gamma_M^t$. Thus, decoding starts in the following order: $l_M, l_{(M-1)}, \dots, l_1$. Let l_k denote the transmission from EHD D_k to the HAP, and Γ_k^t denote the SINR at the HAP for transmission l_k . The transmission of EHD D_k with received power γ_k^t is decoded successfully if the following inequalities are satisfied,

$$\Gamma_M^t = \frac{\gamma_M^t}{\sigma_0^2 + \sum_{i=1}^{M-1} \gamma_i^t} \geq \beta \quad (4)$$

$$\Gamma_{(M-1)}^t = \frac{\gamma_{(M-1)}^t}{\sigma_0^2 + \sum_{i=1}^{M-2} \gamma_i^t} \geq \beta \quad (5)$$

$$\vdots \quad (6)$$

$$\Gamma_{(M-k+1)}^t = \frac{\gamma_k^t}{\sigma_0^2 + \sum_{i=k-1}^{M-1} \gamma_i^t} \geq \beta \quad (7)$$

where σ_0^2 is the ambient noise power and β is the SINR threshold for a required data rate. In the foregone example, in order to decode the signal of EHD D_k successfully, the HAP has to decode and cancel signals with the stronger received power first. On the other hand, if a signal fails

to meet its SINR constraint, then the signal and subsequent transmissions are considered unsuccessful. Lastly, we define the set $\mathcal{K}(S_i, \omega) \subseteq \mathcal{C}(S_i, \omega)$ to contain all transmissions that are decoded successfully by the HAP in uplink slot ω .

IV. THE PROBLEM

Our problem is to determine an uplink transmission schedule that maximizes the expected throughput at the HAP. Let $F^t(S_i)$ be the system throughput if the HAP uses transmission schedule S_i in frame t . The system throughput is the sum of the throughput of all upload slots $\omega = 1, \dots, |S_i|$. For each upload slot, it is the sum of throughput of all successful transmissions $l_k \in \mathcal{K}(S_i, \omega)$. Formally, $F^t(S_i)$ is defined as,

$$F^t(S_i) = \sum_{\omega=1}^{|S_i|} \sum_{l_k \in \mathcal{K}(S_i, \omega)} \mathcal{R}_k^t \frac{\tau_U}{|S_i|} \quad (8)$$

where the asymptotic data rate \mathcal{R}_k^t of transmission l_k is defined as $\mathcal{R}_k^t = B \log_2(1 + \Gamma_k^t)$, where B is the channel bandwidth. Our problem is find the ‘best’ schedule $S \in \Phi$, denoted as S^* , that yields the maximum expected throughput $F(S)$. Formally, our problem is as follows,

$$S^* = \arg \max_{S \in \Phi} \mathbb{E}[F(S)] \quad (9)$$

V. A DISCRETE OPTIMIZATION APPROACH

We propose an algorithm based on discrete stochastic optimization [13], see Algorithm 1. The *basic* idea is to view the set of transmission schedules in Φ as the states of a Markov chain. If a transmission schedule or state has a high reward, then this state will be visited more frequently than others. We say that this state has a high reward or occupancy probability. Our algorithm operates over N episodes. Each episode $n \in \{1, \dots, N\}$ consists of two superframes. Each superframe is further divided into T frames. Recall from Section III that a frame $t \in 1, \dots, T$ consists of a charging phase and a transmit phase. Each frame will be used to obtain the sample average reward of a transmission schedule. To represent the occupancy probability of the transmission schedules in Φ in episode n , we define the one dimensional probability vector $\mathcal{P}[n] \in [0, 1]^{| \Phi |}$. Also, let $\mathcal{P}[n, j]$ be the occupancy probability of transmission schedule $j \in \Phi$. For example, given $\Phi = \{S_1, \dots, S_M\}$, then we have $\mathcal{P}[n] = [\mathcal{P}[n, 1], \dots, \mathcal{P}[n, M]]^T$. We note that for any episode n , the following condition holds: $\sum_{m \in \Phi} \mathcal{P}[n, m] = 1$. Next, we present the notation used to identify a transmission schedule. Define S^n as the transmission schedule selected in episode n , and a two dimensional matrix $\theta = \{e_1, e_2, \dots, e_M\}$, where $e_m \in \{0, 1\}^{| \Phi |}$ is a column vector with its m -th element set to one and all other elements are zero. For example, if we have $M = 3$ transmission schedules in Φ , then we have $\theta = \{[1, 0, 0], [0, 1, 0], [0, 0, 1]\}$; note that for each vector or column, the entry with a value of one identifies the transmission schedule in question. Let $\mathcal{A}[n] \in \theta$ denote the selected transmission schedule in episode n . As an example, assume we have selected the first transmission schedule in Φ , namely $\mathcal{A}[n] = [1, 0, 0]$ or $S^n = S_1$. If instead we have

$\mathcal{A}[n] = [0, 1, 0]$, then this means the selected transmission schedule in episode n is $S^n = S_2$. In each episode, the occupancy probability is updated as follows,

$$\mathcal{P}[n+1] = \mathcal{P}[n] + \mu[n+1](\mathcal{A}[n+1] - \mathcal{P}[n]) \quad (10)$$

where the *step size* is $\mu[n] = 1/n$, meaning it decreases with increasing number of episodes. To gain some intuition of (10), consider the following example. Let there be ten episodes and transmission schedules S_1 and S_2 . Assume S_1 has been used eight out of ten times. Then its occupancy probability will be 0.8 at episode $n = 10$. Next, we make specific the reward of each transmission schedule. Let $Q[n, S^n]$ be the reward of the selected transmission schedule S^n in episode n . We note that the reward is the average system throughput over T frames based on Equ. (8). Formally,

$$Q[n, S^n] = \frac{1}{T} \sum_{t=1}^T F^t(S^n) \quad (11)$$

Algorithm 1: Pseudocode of our solution

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1  $S^0 = i = \mathcal{U}(\Phi)$ 
2  $\mathcal{P}[0, i] = 1, \mathcal{P}[0, m] = 0$  for all  $m = 1, \dots, M \setminus i$ .
3 for  $n = 0, 1, \dots, N$  do
4   for  $t = 1, \dots, T$  do
5     Use  $S^n$  and calculate  $F^t(S^n)$ 
6   end
7   Obtain reward  $Q[n, S^n]$  as per Equ. (11)
8    $\hat{S}^n = \mathcal{U}(\Phi \setminus S^n)$ 
9   for  $t = 1, \dots, T$  do
10    Use  $\hat{S}^n$  and calculate  $F^t(\hat{S}^n)$ 
11  end
12  Obtain reward  $Q[n, \hat{S}^n]$  as per Equ. (11)
13  if  $Q[n, S^n] > Q[n, \hat{S}^n]$  then
14    set  $S^{n+1} = S^n$ 
15  else
16    set  $S^{n+1} = \hat{S}^n$ 
17  end
18   $\mathcal{P}[n+1] = \mathcal{P}[n] + \mu[n+1](\mathcal{A}[n+1] - \mathcal{P}[n])$ 
19 end
20 Return  $S^* = \arg \max_{s \in \Phi} \mathcal{P}[N+1, s]$ 

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We are now ready to explain Algorithm 1 in detail. The algorithm starts by selecting an initial transmission schedule S^0 uniformly from Φ , see line 1. Here, the function $\mathcal{U}(\Phi)$ is a function that returns a transmission schedule S_i from the set Φ in a uniform manner. Also, the initially selected schedule has an occupancy probability of one. The occupancy probability of other transmission schedules is set to zero; see line 2. Our algorithm runs for N episodes. In each episode n , see line 3 to line 19, we calculate the average reward of the given schedule S^n , see line 4 to line 7. After that, we uniformly select another transmission schedule \hat{S}^n , see line 8, and calculate its average reward over T frames, see line 9 to line 12. Then starting from line 13 to line 17, the algorithm compares the average reward

of the given schedule S^n against the randomly selected schedule \hat{S}^n , and selects the transmission schedule with the higher reward. Lastly the occupancy probability $\mathcal{P}[n]$ is updated in line 18. As we mentioned earlier, the optimal transmission schedule achieves the highest occupancy probability. This is exactly line 20, which returns the schedule S^* that has the maximum occupancy probability in $\mathcal{P}[N+1]$. We note that Algorithm 1 calculates the reward using Equ. (11) for each frame $t \in \{1, \dots, T\}$ of each episode $n \in \{1, \dots, N\}$. This means the time complexity of Algorithm 1 is $\mathcal{O}(TN)$.

VI. EVALUATION

Table I lists our simulation parameters. Nodes are deployed on a circle with a radius of 10 meters, and the HAP is placed at the center. In the first experiment, we aim to study the convergence of our algorithm to the best schedule. To this end, we place three EHDs D_1 , D_2 and D_3 at 6.4, 3.1 and 4.7 meters away to the HAP, respectively. In this case, we obtain five possible transmission schedules: $S_1 = [(D_1, D_2, D_3)]$, $S_2 = [(D_1), (D_2, D_3)]$, $S_3 = [(D_2), (D_1, D_3)]$, $S_4 = [(D_3), (D_1, D_2)]$ and $S_5 = [(D_1), (D_2), (D_3)]$. We record the occupancy probability of these schedules for the following SINR threshold β values: is 0, 2, 4 dB. Referring to Figure 2, the occupancy probability of all schedules fluctuates significantly initially. This is because the initially selected schedule has an occupancy probability of one but it may not have a high reward. Consequently, the HAP continues to select other schedules. In addition, the step size $1/n$ is large initially. Therefore, in each episode, the schedule with a large reward will have a large occupancy probability. With increasing number of episodes, the step size reduces, which allows our algorithm to converge to the schedule with the best reward. As we can see from Figure 2, our solution converges, i.e., finds the best schedule, after 100 episodes.

We see from Figure 2(a) and 2(c) that there exists a best schedule for each SINR threshold. In Figure 2(a) and Figure 2(b), when $\beta = 0$ dB and 2 dB, schedule $[(D_1, D_2, D_3)]$ has the highest occupancy probability. However, when $\beta = 4$ dB, see Figure 2(c), the occupancy probability of schedule $[(D_1, D_2, D_3)]$ decreased significantly. In contrast, schedule $[(D_3), (D_1, D_2)]$ becomes the best schedule. This is expected because when the SINR threshold β is small, more transmitting devices can co-exist together in the same time slot, which results in a higher throughput. Conversely, a large β value results in more SIC failures.

Next, we study the average throughput of all five schedules for different SINR threshold values. We implement a brute-force method to calculate the average throughput by running each schedule for 1000 frames as per Equ. (11). From Figure 3(a), we can see that the performance of these schedules is consistent with the occupancy probability shown in Figure 2. Specifically, when $\beta = 0$ dB, schedule $[(D_1, D_2, D_3)]$ achieves an average throughput of 8.3 Mbps. It also has the highest occupancy probability of around 0.97 as shown in Figure 2(a). This is expected as the difference in received power can be low in order for SIC to be successful.

TABLE I
SIMULATION PARAMETERS

Parameter	Value(s)
Proportion of charging duration and data transfer duration in a frame	1:1
The HAP's transmit power P	30 dBm (1 Watt)
Antenna gain for HAP and EHDs	3 dBi and 2 dBi as per the Wasp mote datasheet ²
Slow fading variance σ	3 dB
Path loss \mathcal{L}_0 at reference distance 1 m	30 dB
Path loss exponent α	2.5
Parameters for non-linear energy harvesting model ζ_1 , ζ_2 and ζ_3 [12]	150, 0.014 and 24mW
Noise variance σ_n^2	-80 dBm
Number of episodes N	500
Number of frames T in each superframe	10
Bandwidth B	1 MHz
SINR threshold (dB) β	0, 1, 2, 3, 4

² <http://www.libelium.com>

Then with an increasing SINR threshold from 0 dB to 2 dB, the throughput of schedule $[(D_1, D_2, D_3)]$ experiences a significant decrease from 8.3 to 6.8 Mbps, which also causes its occupancy probability to drop from nearly 1.0, see Figure 2(a), to 0.6, see Figure 2(b). Finally, when β exceeds 3 dB, schedule $[(D_3), (D_1, D_2)]$ achieves an average throughput of 5.6 Mbps, which outperforms schedule $[(D_1, D_2, D_3)]$. This means schedule $[(D_3), (D_1, D_2)]$ has the highest occupancy probability of around 0.6.

In this last experiment, we first obtain the best schedule using our solution and compare its throughput to a TDMA schedule and Slotted Aloha. Briefly, a TDMA schedule contains only one device in each upload slot. For Slotted Aloha, EHDs randomly select a slot to transmit. We study different SINR threshold β values and number of EHDs K . The average system throughput is calculated over 500 frames as per Equ. (11). Figure 3(b) shows the impact on the average throughput for different SINR thresholds. We consider the topology with three EHDs. We notice that with the increase of SINR threshold, both of the best schedule and Slotted Aloha schedule experience throughput degradation. As we explained earlier, a large β value means there needs to be a high received power difference in order to ensure a successful SIC. As a result, there is a higher chance of SIC failures. In addition, when $\beta = 0$ dB, the throughput obtained by the best schedule is 1.5 times of the throughput by Slotted Aloha, and nearly twice the throughput of TDMA. When $\beta = 2$ dB, the best schedule outperforms Slotted Aloha by 2 Mps. The performance of Slotted Aloha is the same as TDMA when $\beta = 4$ dB. Our schedule outperforms them by 0.5 Mbps.

Figure 3(c) compares the average throughput of different schedules over different number of EHDs. The SINR threshold β is set to 2 dB. First, note that since β is small, the probability of SIC failure is low. Therefore, the Slotted Aloha schedule with three slots outperforms the case with four slots. This is because there are more EHDs in each time slot. Moreover, when $K = 3$, TDMA outperforms both Slotted Aloha with

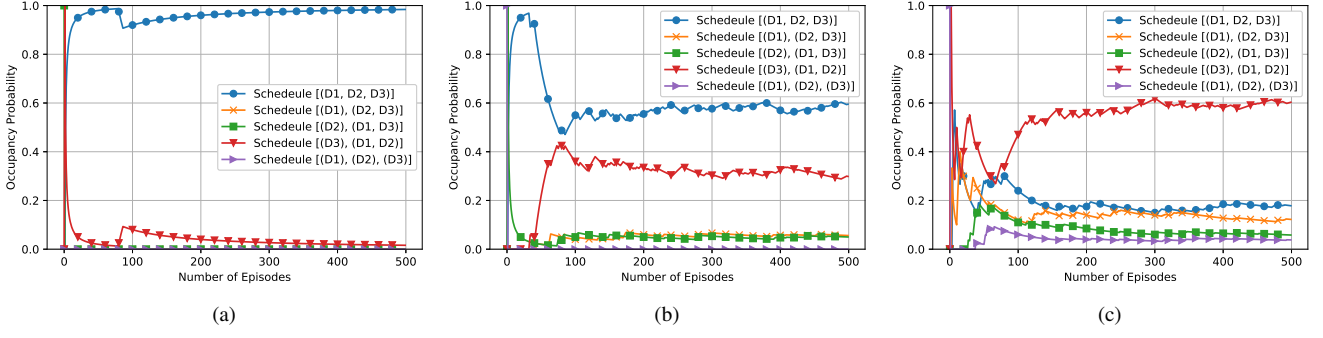


Fig. 2. Occupancy probability for three EHDs with five schedules under different SINR thresholds: (a) $\beta = 0$ dB, (b) $\beta = 2$ dB, (c) $\beta = 4$ dB.

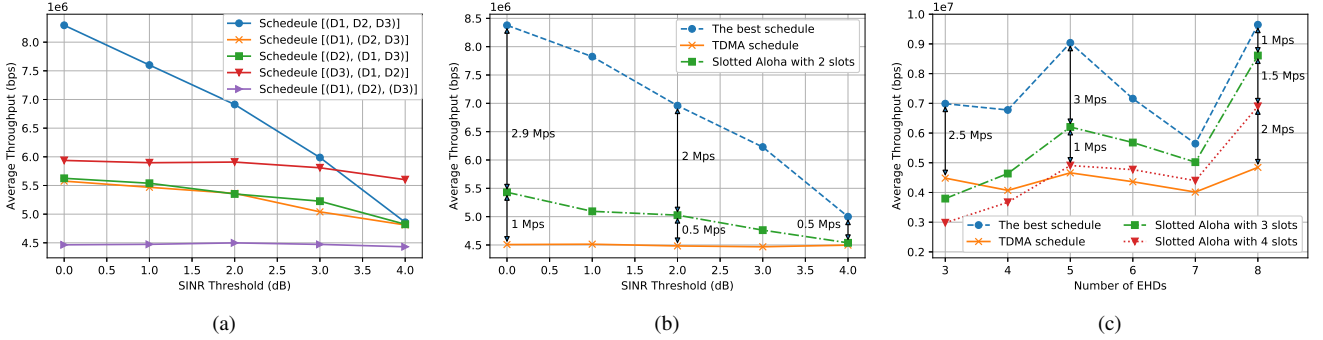


Fig. 3. (a) Average system throughput for $K = 3$ EHDs with five schedules under different SINR thresholds; (b) A comparison of average throughput when there are $K = 3$ EHDs under different SINR thresholds; (c) Average system throughput with $\beta = 2$ dB versus number of EHDs.

three and four slots. The reason is because Slotted Aloha randomly select EHDs into different slots, which may lead to idle slot(s). Consequently, the resulting schedule has a low throughput. Figure 3(c) also shows that the best schedule from our solution achieves the highest throughput, which outperforms Slotted Aloha by 50% when there are five EHDs.

VII. CONCLUSION

An important problem in future IoT systems is to collect data from RF harvesting devices. To this end, we consider the problem of scheduling uplink transmissions from these devices. We outline a novel problem whereby a HAP has to select the best transmission schedule without CSI knowledge. This problem is significant because it allows a HAP to collect data without first collecting CSI. We outline a discrete optimization approach and verified it via simulation. Our results show that it is able to pick a transmission schedule that yields the highest expected sum-rate.

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